Chapter 7
Predicting elephant (*Loxodonta africana*) presence in a Southern African agricultural landscape from the spatial heterogeneity of NDVI [6]

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Abstract

We investigated whether and how the probability of African elephant (*Loxodonta africana*) presence was related to spatial heterogeneity of vegetation cover (estimated from a remotely sensed normalised difference vegetation index (NDVI) from Landsat TM) in space and over time in the agricultural landscape in northwestern Zimbabwe between the early 1980s and early 1990s. A new approach was used to characterise spatial heterogeneity based on the intensity (i.e., the maximum variance exhibited when a spatially distributed landscape property such as vegetation cover is measured with a successively increasing window size or scale) and dominant scale (i.e., the scale or window size at which the intensity is measured). This approach was implemented using a wavelet transform. The results showed that spatial heterogeneity could explain 80 % and 93 % of the variance of the probability of elephant presence in the early 1980s and early 1990s respectively. The changes in spatial heterogeneity predicted 89 % of the variance of the change in elephant presence between the 1980s and 1990s. These results imply that if elephants are to be conserved in agricultural landscapes, it is important that wildlife management strategies aimed at sustaining wildlife species in agricultural landscapes take into account the level of spatial heterogeneity of natural vegetation. In addition, the results imply the wavelet transform-derived spatial heterogeneity could improve the prediction of ecological patterns.

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[6] Based on: The spatial distribution of elephants (*loxodonta africana*) in relation to the spatial heterogeneity of vegetation cover in a Southern African agricultural landscape, paper presented to the conference on Scales and Dynamics in Observing the Environment, 10-12, September 2003, Nottingham, UK. Also submitted to: Remote Sensing of Environment

7.1 Introduction

Community based natural resource management (CBNRM) programmes in the agricultural landscapes of Southern Africa such as the Communal Areas Management Programme For Indigenous Resources (CAMPFIRE) in Zimbabwe (Hoare and Du Toit 1999, Hulme and Murphree 2001, Logan and Moseley 2002) owe their existence to the persistence of wildlife species throughout these landscapes. However, wildlife species persistence in agricultural landscapes of Southern Africa, particularly in Zimbabwe, is increasingly being threatened by agricultural field expansion into the natural habitats (Cumming 1982, Cumming and Lynam 1997, Hoare 1999, Hoare and Du Toit 1999). The critical question for wildlife managers and ecologists is: how can wildlife persistence outside the wildlife reserves be ensured in the face of expanding agriculture? In other words, in what kind of agricultural landscape can wildlife species thrive? The answer is in understanding the kind of habitat conditions that can make elephants persist within the unique context of agricultural landscapes where arable fields cut up natural habitats into discontinuous patches of different spatial arrangements. In such a landscape, it is not only the amount of natural habitat that is important for wildlife species persistence, but the spatial arrangement of habitat patches also becomes particularly critical. Thus, to ensure wildlife species persistence in agricultural landscapes it is critical to understand how they respond to spatial heterogeneity (i.e., the patchiness in vital landscape properties such as vegetation cover (Legendre and Fortin 1989, Pickett and Rogers. 1997, Gustafson 1998) that is imposed by the agricultural fields onto the natural habitat. Consequently, the need for research to characterise wildlife species response to spatial heterogeneity in agricultural landscapes is critical.

Although empirical and theoretical literature recognises the importance of spatial heterogeneity to wildlife distribution (Turner 1989, Johnson*, et al.* 1992, Kareiva and Wennergren 1995, Turner*, et al.* 1997, Lynam and Billick 1999, Adler*, et al.* 2001), an understanding of the levels of spatial heterogeneity at which specific wildlife species can persist in agricultural landscapes is still rudimentary. This may stem from the lack of clarity in the characterisation of spatial heterogeneity (Sparrow 1999).

In other words, this suggests that spatial heterogeneity needs to be properly characterised even before the wildlife response to spatial heterogeneity can be understood.

The quantification of spatial heterogeneity is an empirical approach based on observed data, thus it is a forerunner to testing specific hypotheses about ecological patterns (Perry*, et al.* 2002). In this regard, ecologists have traditionally quantified spatial heterogeneity from remote sensing imagery by using two basic approaches: (a) the direct image approach, where straight reflectance or reflectance indices of remote sensing images are used to quantify spatial heterogeneity, using the original pixel size of the image (Goodchild and Quattrochi. 1997); and (b) the cartographic or patch mosaic approach, where the image is subdivided into homogeneous mapping units through classification (Gustafson 1998). The first approach assumes that spatial heterogeneity is at the pixel size of the image and, in this case, it is only the reflectance values that are important. The limitation of this approach is that its choice of scale (i.e., window size) is arbitrary, thus it is subjective. Alternatively, using the patch mosaic approach to quantify spatial heterogeneity assumes a collection of discrete patches. Based on this approach, characterisation of spatial heterogeneity is highly dependent on the initial definition of mapping units by the researcher (Turner 1989). The limitation of this approach is that patches have abrupt boundaries and the variation within the patches is assumed to be irrelevant (McGrigal and Cushman 2002). The patch mosaic model is parsimonious and has therefore become the operating paradigm. It is particularly valid where landscape patches have crisp boundaries, as with the regular landscapes of Europe (Pearson 2002). However, the model poorly represents spatial heterogeneity in landscapes that are characterised by gradients rather than discrete patches, for instance in savanna landscapes (Pearson 2002), and this leads to both loss of information and the introduction of subjectivity. Nevertheless, alternative approaches to characterise spatial heterogeneity remain underdeveloped.

In view of the limitations in the approaches mentioned above, we develop a new approach to characterising spatial heterogeneity, based on intensity, as well as the dominant scale and apply it to predict wildlife species distribution, particularly that of the African elephant (*Loxodonta africana*) in an agricultural landscape. Intensity is defined as the

maximum variance exhibited when a spatially distributed landscape property is measured with a successively increasing window size or scale. For example, measuring the variance in percent canopy cover along a 100 m long transect in a tree plantation with 10 m wide tree stands (with uniformly high canopy cover) that evenly interchange with 10 m wide bare ground (with zero canopy cover) at a successively increasing window size, starting from 1 m up to 100 m, would yield the maximum variance at a window size equal 10 m. This maximum variance is the intensity of spatial heterogeneity. It is the scale or window size where the maximum variance in the landscape property is measured that is defined as the dominant scale of spatial heterogeneity. In other words, intensity and dominant scale of spatial heterogeneity are properties of a landscape that are inseparable. In this case, the dominant scale of spatial heterogeneity coincides with the dominant patch dimension (i.e., size of tree stands and bare ground) in the landscape. Note that our definition of scale follows that of Levin (1992) and Rietkerk*, et al.* (2002) who define scale as the window or dimension (e.g., m, km, m^2, km^2) through which the landscape may be observed either in remote sensing images or by direct measurement. In this study, scale is treated as a linear dimension, e.g., m, km. We therefore propose that spatial heterogeneity be defined and quantified using both intensity and the dominant scale. Of course, grain (i.e., the initial observation scale or window size at which the data is collected) and extent (overall size of the study area) limits the range of the dominant scale that can be detected (Wiens 1989).

Furthermore, in order to properly elucidate the centrality of the intensity and the dominant scale in the characterisation of spatial heterogeneity, we present a simulation of tree canopy cover along three artificial transects (fig. 7.1). The tree canopy cover along by the three artificial transects that stretch over 1000 m is sampled at an interval of 1 m. Thus, the interval of 1 m defines the grain (observation scale) while the 1000 m defines the extent (overall transect length). The transects 1 and 2 have a dominant scale of spatial heterogeneity of 100 m, i.e., maximum variance is recorded at the window size of 100 m whereas transect 3 has a dominant scale of 200 m. The dominant scale of spatial heterogeneity in transects 1 and 2 is equal but the intensity of spatial heterogeneity is
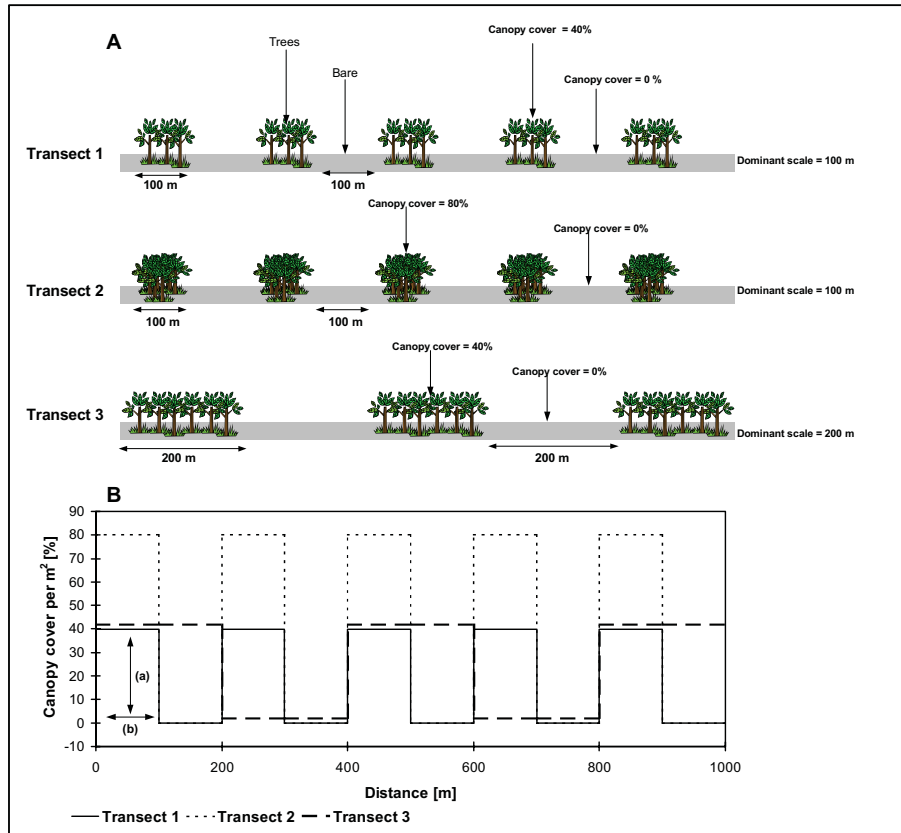
Figure 7.1: Part (A) are transects with alternating spaces of trees and bare ground and part (B) shows the simulation tree canopy cover along each transect assuming that the cover measurements are made after every 1 m (i.e., grain = 1 m) and an extent of 1000 m. For example, the (a) intensity (maximum variance) of transect 1 occurs at (b) a dominant scale of 100 m.

different. Next, a look at transects 1 and 3 shows that they have equal intensity of spatial heterogeneity but have different dominant scales of spatial heterogeneity. Therefore, characterizing spatial heterogeneity in this example is incomplete if only the intensity or the dominant scale of spatial heterogeneity is considered. Thus, we propose that both the intensity and dominant scale describe the spatial heterogeneity of a

137

landscape. This method of characterising spatial heterogeneity in the landscape was developed and tested by Murwira and Skidmore (2003)

In this study, the objective was to use a wavelet transform to quantify the spatial heterogeneity of a normalised difference vegetation index (NDVI) and then test whether the wavelet-quantified spatial heterogeneity consistently explain wildlife species distribution in a landscape, particularly that of the African elephant (*Loxodonta africana*) in northwestern Zimbabwe between the early 1980s and early 1990s. Specifically we tested: (1) whether the probability of African elephant presence in different parts of the landscape was consistently and significantly related the dominant scale and intensity of spatial heterogeneity during the two dates and, (2) whether changes in the probability of elephant presence in different parts of the landscape, between the early 1980s and early 1990s, were related with changes in the dominant scale and intensity of spatial heterogeneity. Murwira and Skidmore (2003) demonstrated the utility of wavelets in characterising spatial heterogeneity from a dominant scale and intensity perspective.

The African elephant was selected for several reasons. Firstly, the Africa elephant is a keystone species of the African savanna (Hoare and Du Toit 1999) that need to be conserved. Secondly, the African elephant is on the list of the world's threatened species (IUCN 2002) and is considered a conservation priority. Thirdly, the study area has been the only agricultural landscape in Zimbabwe outside the protected wildlife reserves with a healthy expanding elephant population (Cumming 1981). Nevertheless, this situation is increasingly being threatened by agricultural field expansion following the continual eradication of tsetse (Glossina sp.) since the 1960s. Thus, there is need of interventionist strategies to conserve the elephant. Fourthly, water is not a limiting factor in the study area (Cumming 1981), and since the African elephant is a habitat generalist (Kingdon 2001) it has a potential of being anywhere in the study area and it can be hypothesised that the level of spatial heterogeneity mainly affect its distribution. Also, good survey data exists on the spatial distribution of the African elephant in the study area.

7.2 Materials and Methods

Study area

This study is based on the Sebungwe region in the northwestern part of Zimbabwe (fig. 7.2). The Sebungwe region is composed of undulating topography with the average elevation of between 700 – 800 m above sea level. The region is characterised by a single wet season (November to March) with a mean annual rainfall of 680 – 700 mm, as well as a long dry season (April to October). Savanna woodlands and grasslands characterise the main natural land cover, i.e., Miombo woodland dominated by *Brachystegia spp.* and *Julbernardia globiflora,* Mopane dominated by *Colophospermum mopane,* Faidherbia woodland dominated by *Faidherbia albida,* Miombo-Mopane with co-dominance of *Brachystegia spp.* and *Julbernardia globiflora* and *Colophospermum mopane*, as well as, Setaria dominated by *Setaria incrassata, Ischaemum afrum* and *Dicathium papillosum* (Timberlake*, et al.* 1993) (fig. 7.2b). The floristic-physiognomic vegetation units do not change over time, representing the vegetation classes that would be there in an undisturbed environment (Timberlake*, et al.* 1993). Therefore, the boundaries do not change within a matter of decades.

The Sebungwe contains of five wildlife reserves, interspersed with communal lands (fig. 7.2a) with varying degrees of agriculture and varying degrees of wildlife presence. Communal lands are a land category characterised by collective or community land ownership and they are subdivided into administrative or management units called wards (fig. 7.2a). In the communal lands wildlife presence is affected by the ecological conditions such as the availability of vegetation cover, and also poaching and human disturbance, and also poaching and human disturbance rather than by conservation measures or laws like in the wildlife reserves, i.e., wildlife species are present provided there are necessities such as enough cover and water. Wildlife has to cross the communal lands when moving between the wildlife reserves. Thus, the communal lands also provide wildlife corridors that link the wildlife reserves (Cumming and Lynam 1997).
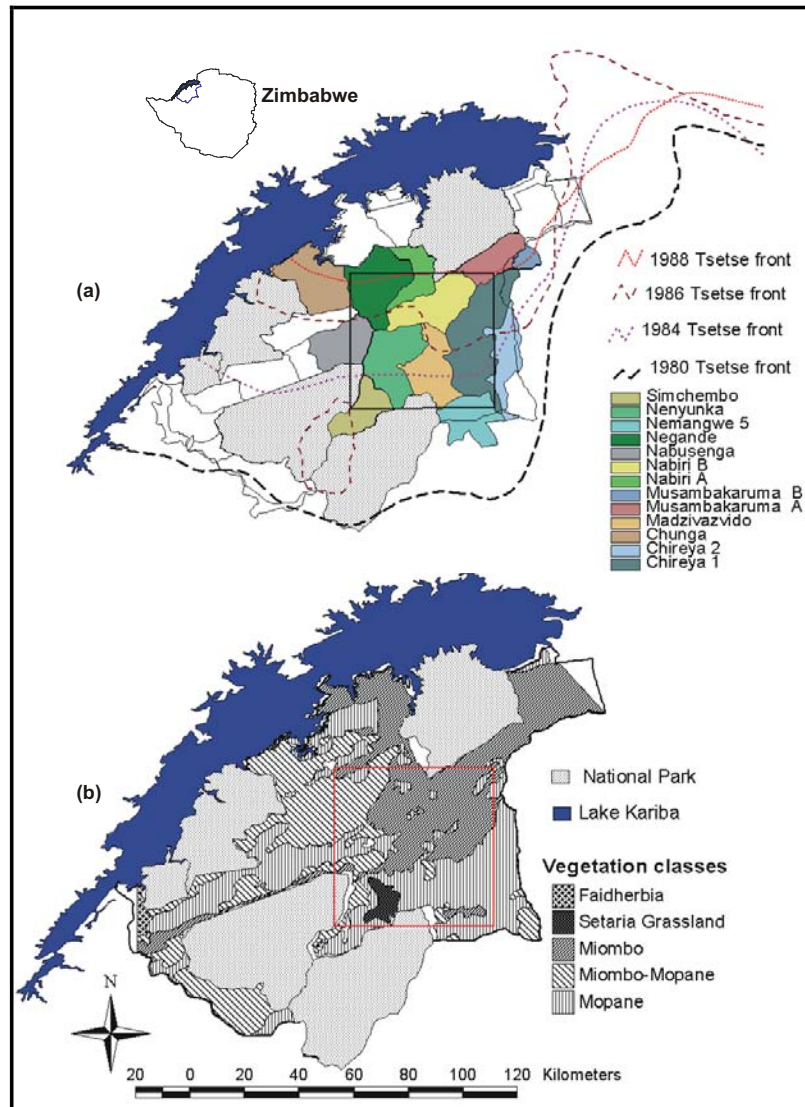
Figure 7.2: The location of the Sebungwe region in Zimbabwe and (a) the wards, national parks and the history of the progression of tsetse eradication (source: Tsetse and Trypanosomiasis control branch, Harare) and (b) the physiognomic-floristic vegetation classes in the communal lands based on (Timberlake and Nobanda 1993). The square box is a 61 km x 61 km area selected for this study.

140

Moreover, the Sebungwe landscape evolved from a complex of different historical forces linked to the eradication of tsetse fly (*Glossina* sp.) and the related land use (fig. 7.2)a. Historically, the Sebungwe region was home to both tsetse fly and a wide range of wildlife species until the 1960s when the tsetse belt began to continually dwindle as a consequence of the tsetse eradication programme that was meant to enable livestock ranging and arable agriculture, thereby relieving population pressure from elsewhere in the country. As tsetse fly was progressively destroyed since the 1960s, the valley began to be increasingly occupied by farmers (Cumming and Lynam 1997). By the mid-1980s immigration had accelerated and the threat of arable agriculture on the persistence of wildlife began to increase in parts of the Sebungwe (Cumming and Lynam 1997). The results were the varying degrees wildlife presence as a function of varying levels of arable agriculture (Hoare and Du Toit 1999).
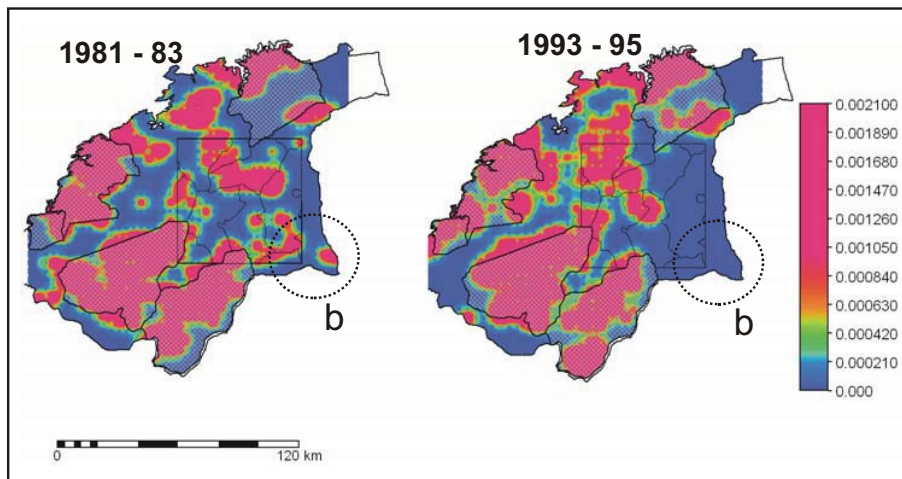

Figure 7.3: The probability of elephant presence within a 3 km radius in the study area in 1981-83 and 1993-95 and the 61 km by 61 km square box selected for this study. The ellipse (b) illustrates an area where there was a major noticeable decrease in the probability of elephant presence between 1981-83 and 1993-95.

This study is based on a 61 km x 61 km area (square box in fig. 7.2), mainly covering the communal lands. This study area was considered large enough for studying elephant distribution in the

Sebungwe. Specifically, elephants in the Sebungwe region have an estimated range of between 83 km^2 to 263 km^2, approximating a horizontal length scale (horizontal dimension) of 9.1 km and 16.2 km, respectively (Guy 1976a, Dunham 1986). This makes the extent of the study area, i.e., 3721 km^2, which is at least 14 times the estimated range of the elephant in the Sebungwe large enough to study elephant distribution.

Elephant data

The data on the spatial distribution of elephants in the 1980s and 1990s were determined using respectively a combined 1981-1983 data set, and 1993-1995 data set. These data were obtained from the point location data from the analyses of Sebungwe aerial surveys by Cumming and Lynam (1997) and made available by WWF in Harare. The locational error of the elephant sightings was within 500 m, i.e. 250 m on the side of the aircraft and 1000 m along the flight path (Cumming and Lynam 1997). The aerial surveys were carried out in the dry season, i.e., between August and October of the relevant years. This was considered an appropriate period for studying the effect of spatial heterogeneity on elephant distribution because the crop fields are fallow during this time. Crop fields tend to attract the elephants outside their normal natural range, thus making wet season (October to March) data much less reliable for assessing the effect of spatial heterogeneity. In other words, an area that can be suitable for the elephant in the dry season can safely be assumed to be suitable in the wet season. The data were in digital point map format. We considered the elephant distribution map of our study area R as a spatial point pattern (Diggle 1983). Each point where elephants were observed is called an event. We calculated the first-order intensity function $\lambda(x)$ for the elephant point map to give an expected number of events per unit area(Fotheringham, *et al.* 2000):

$$\lambda(x) = \lim_{r=0} \frac{E(N(C(x,r),X))}{\pi r^2} \qquad (7.1)$$

where *E(N)* is the expected number of events in the study area considered and *C(x,r)* a circular sub-region of R located at *x* with a radius *r*. A kernel function was used in this study with *r* equal to 3000 m based on an exploratory analysis in S-PLUS software (Lam 2001). This kernel radius was also large enough to overcome any locational errors in elephant

sightings. We then normalised λ(x) by dividing it by the expected number of events in R to produce a normalised or probability function λ*n*(*x*) (Fotheringham*, et al.* 2000):

$$\lambda n(x) = \frac{\lambda(x)}{E(N(R,X))} \tag{7.2}$$

Next, λ*n*(*x*) was used to estimate the spatial distribution of elephants in the study area during the 1980s and 1990s. The point pattern analysis method was used because it is spatially explicit and gives weight to elephant location rather than absolute numbers: the aim was to determine whether spatial heterogeneity affects the presence of at least a single elephant and since the elephant survey data sets were combined, adding the total number of observed elephants of the years would give a false impression about absolute elephant abundance. Fig. 7.3 shows the maps of the probability of elephant presence in the early 1980s and the early 1990s.

Remote sensing data

The amount of vegetation cover or biomass was estimated from NDVI derived from the readily available TM images of 19 October 1984 and the one of 16 April 1992:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{7.3}$$

where *NIR* and *R* are respective spectral reflectance values in the near infrared and the red. Data were normalised to the range of 0 to 255 in order to facilitate data handing in image processing software. Relative radiometric correction of the two images was done using the regression method based on pseudo variant objects such as water bodies, airstrips and roads (fig. 7.4). This was done to minimise atmospheric effects in the analysis of spatial heterogeneity from the NDVI images of the two different dates. Fig. 7.5 shows the NDVI images of the 61 km x 61 km study area. As mentioned earlier, NDVI was used because it is an
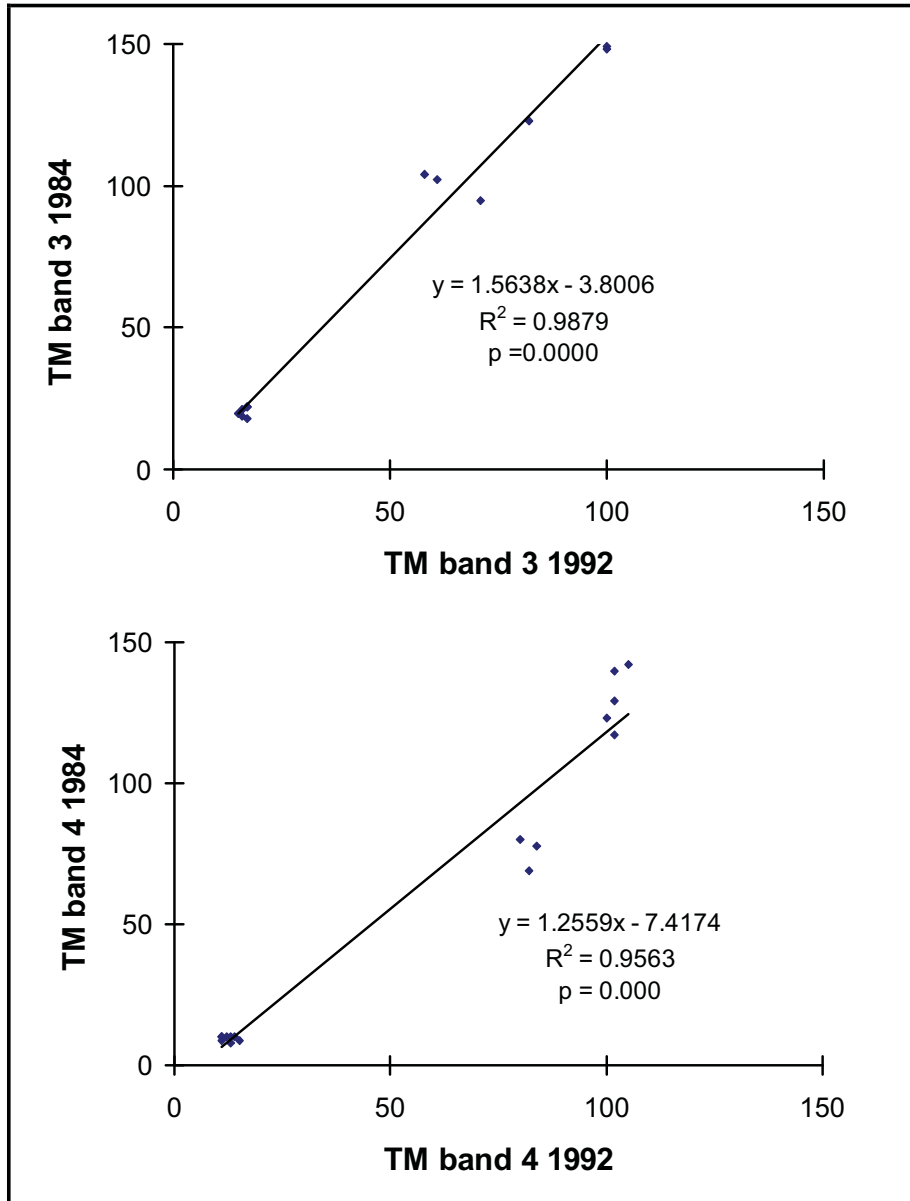
Figure 7.4: Relationship between the DN values of sampled pseudo variant objects between the Landsat TM images of 19 October 1984 and 16 April 1992.
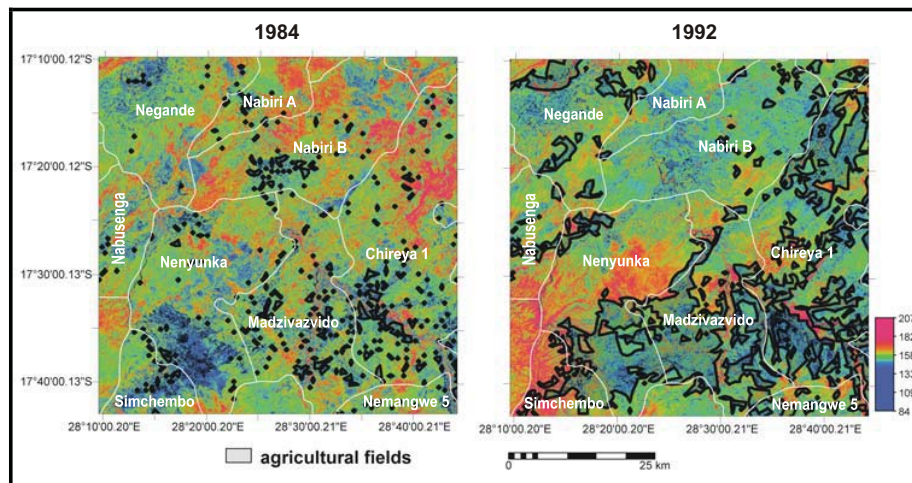
Figure 7.5: Map showing the 1984 and 1992 NDVI maps of the 61 km by 61 km square box overlaid with layers of ward boundaries and agricultural fields. Low NDVI values indicate low vegetation cover and high NDVI values indicate high vegetation cover within a 0 to 255 range. The NDVI values were stretched the same way for display to make them comparable but the NDVI ranges were different for 1984 and 1992.

established index for estimating vegetation quantity (Walsh, *et al.* 1997, Walsh, *et al.* 2001). Also, NDVI have been shown to provide an effective measure of photosynthetically active biomass (Tucker and Sellers 1986, Los. 1998, Turner, *et al.* 1999, Birky 2001, Hill and Donald 2003) and it is an index of total vegetation biomass (Goward and Dye 1987). Also, NDVI is also strongly related to the extent of vegetation cover and therefore, can be used to detect land cover changes (e.g., woodland replacement with agriculture) and can also be used as an indicator of spatial heterogeneity in the landscape (Kerr and Ostrovysky 2003). Dry season imagery was used in this study because elephant data was collected in the dry season. In addition, it is easier to distinguish between fallow agricultural fields and natural vegetation using NDVI in the dry season than in the wet season, i.e., high NDVI values are expected for natural vegetation and lower NDVI values are expected for fallow agricultural fields (fig. 7.5). Thus, it is apparent in fig. 7.5 that areas with low NDVI mainly coincide with agricultural fields. It was assumed that the time differences between the

145

dates of the wildlife surveys and the satellite images was close enough and therefore, had negligible negative effects on the analysis.

Several advantages were envisaged in using Landsat TM imagery to characterise the spatial heterogeneity for the study of elephant distribution. Most importantly, the spatial resolution or grain of Landsat TM, i.e., 30 m by 30 m was detailed enough to enable the quantification of spatial heterogeneity that is relevant for analysing elephant distribution; generally, the grain should be several magnitudes smaller than the total range of the organism (Sparrow 1999). Since elephants in the Sebungwe region have an estimated range of 83 km^2 to 263 km^2, approximating a horizontal length scale (horizontal dimension) of 9.1 km and 16.2 km, respectively (Guy 1976a, Dunham 1986), the grain of 30 m makes it 300 times smaller than the minimum range of the elephant.

Characterising spatial heterogeneity using wavelets

Wavelet energy (Bruce and Hong-Ye. 1996) was used to quantify the intensity and the dominant scale of spatial heterogeneity in the NDVI images of 1984 and 1992. The determination of wavelet energy begins with a wavelet transform (in this study a Haar wavelet was used), which is defined as the convolution of two wavelet functions, i.e., the *smooth* $\phi(x, y)$ and *detail* $\varphi(x, y)$ functions, and an NDVI image $f(x, y)$ at successive bases, (2^j), i.e., $j = 0,1,2…J$ in the vertical (north-south), diagonal (northeast-southwest and northwest-southeast) and horizontal (east-west) directions for the 2-dimensional data. A wavelet transform results in a set of coefficients where each coefficient is associated with a base level, $j = 0,1,2…J$, a direction and a particular location.

The wavelet approximation $\hat{f}(x, y)$ of the original 2-dimensional function $f(x,y)$ is a sum of the smooths and the detail functions at different bases:

$$\hat{f}(x, y) = S_J(x, y) + \sum_{j=1}^{J} \sum_{dir} D_j^{dir}(x, y) \qquad (7.4)$$

S_J represents the smooth coefficients and D_j^{dir} are the directional (i.e., vertical (north-south), horizontal (east-west) and diagonal (northeast-southwest and northwest-southeast)) detail coefficients. By convention, the grain of $f(x,y)$ is equals to $j = 0$. Therefore, each scale level j corresponds to a window size or scale equals $2^j * s$ where s is the size of the original grain at which $f(x,y)$ is mapped (in this case 30 m, the spatial

146

resolution of Landsat TM). The decision on the magnitude of *J* (i.e., the broadest base or window of focus) is made in advance and depends on how much detail is required in the analysis and also on the size of the image. In this study we selected *J* equals 7, an equivalent of a spatial dimension of 3840 m. Note that the theory and formal treatment of wavelets has been covered exhaustively elsewhere (Mallat 1989, Ogden 1997) and is beyond the scope of this study.

Wavelet coefficients can be positive or negative but the absolute coefficient value measures the magnitude of contrast in *f(x,y)* at a specific location with a base of 2^j. Wavelet energy was calculated as a second moment of the wavelet transform defined as the sum of squares of the coefficients at base 2^j, divided by the sum of squares of all the coefficients in $\hat{f}(x,y)$:

$$E^d_j = \frac{1}{E} \sum_{k=1}^{n/2^j} d^2 j(x,y), j = 1,2,3...J \qquad (7.5)$$

where $d_j(x,y)$ are the detail wavelet coefficients at *j* and position (x,y), *E* is the total sum of squares of $\hat{f}(x,y)$ and $n/2^j$ is the number of coefficients at level *j*. Then, wavelet energy values were plotted against scale and the highest local maxima in the wavelet energy function represented the intensity of spatial heterogeneity while the corresponding scale value represent the dominant scale of spatial heterogeneity (Murwira and Skidmore. 2003).   The detail functions rather than the smooth approximations were used in the analysis because they are scale specific. For example, details at *j* = 1 capture vegetation patches that have a size between 30 m and 60 m. In contrast, smooth coefficients can only capture scales that are equal or greater than 2^j, thus they are not scale specific.

Relating the probability of elephant presence to spatial heterogeneity

The relationship between the probability of elephant presence and the dominant scale and intensity of spatial heterogeneity was tested on the 61 km x 61 km study area, i.e., in the communal lands of the Sebungwe. The individual units of analysis (sampling units) were defined to be the intersection of the ward boundaries and vegetation class boundaries, thereby incorporating variation due to management and ecological factors respectively. These sampling units were obtained by crossing the ward and

vegetation class maps in a Geographical Information system (GIS). The floristic-physiognomic vegetation class map (fig. 7.2) describes the potential vegetation classes, and is therefore constituted by floristic units that are constant over time (Timberlake*, et al.* 1993). All in all, 22 units of analysis were used in this study.

Before the probability of elephant presence was related to the dominant scale and intensity of spatial heterogeneity, the wavelet functions for separate wards, as well as physiognomic-floristic vegetation classes (Miombo, Mopane, Miombo-Mopane and Setaria) were plotted and the dominant scale and intensity information was determined for each unit of analysis. The Faidherbia vegetation class was excluded in the analysis because it covers a very small part of the study area such that not enough coefficients are included in the Faidherbia unit. Then, the probability of elephant presence in each sampling unit was determined by crossing the map of the probability of elephant presence (fig. 7.3) and the map of sampling units defined by wards and vegetation classes and calculating the average probability of elephant presence. The mean probability of elephant presence for each sampling unit of analysis was used as a measure of elephant presence in regression analysis.

Next, regression analysis was used to relate the probability of elephant presence to the dominant scale and intensity of spatial heterogeneity respectively using both the 1980s and 1990s data. In addition, the probability of elephant presence was analysed as a function of the dominant scale and intensity of spatial heterogeneity plus the interaction between the two. Use of data from two dates gave us a possibility to check whether elephant presence was consistently related with the dominant scale and intensity of spatial heterogeneity irrespective of time. The final regression analysis attempted to determine whether there was a relationship between the spatial changes in both dominant scale and intensity of spatial heterogeneity between 1984 and 1992 and the spatial changes in the probability of elephant presence between 1981-83 and 1993-95. To accomplish this, the intensity and dominant scale values of 1984 were subtracted from the respective values of 1992 so that positive values would represent an increase in each respective factor while negative values would represent a decrease in each respective factor between the two periods.

7.3 Results

Spatial heterogeneity in Sebungwe in 1984 and 1992

Fig. 7.6 shows selected wavelet energy functions that illustrate changes in the dominant scale and the intensity of spatial heterogeneity in the study area between 1984 and 1992. Generally, the wavelet energy functions in 1992 had higher values than in 1984. For example, the Setaria typifies changes in both the dominant scale of spatial heterogeneity and intensity of spatial heterogeneity between the two dates. In 1984 the Setaria had larger dominant scales of spatial heterogeneity than in 1992, whereas the intensity of spatial heterogeneity in 1984 was less than in 1992.

Fig. 7.7 shows a multiscale wavelet energy representation of NDVI in the study area in 1984 and 1992. It can be observed that there was a decrease in the dominant scales of spatial heterogeneity in the selected Setaria analysis units from 1920 m and 960 m in 1984 to 240 m and 480 m in 1992 respectively in Nenyunka and Madzivazvido. In contrast, it can be observed that there was no change in the dominant scale of spatial heterogeneity for the selected Miombo-Mopane analysis unit in Madzivazvido between 1984 and 1992.

Relationship between elephant presence and spatial heterogeneity in space

Fig. 7.8 shows that there were significant ($p < 0.05$) quadratic relationships between the probability of elephant presence and the dominant of spatial heterogeneity, as well as between the probability of elephant presence and the intensity of spatial heterogeneity both in 1980s and 1990s. The relationship between the dominant scale of spatial heterogeneity and the probability of elephant presence is such that there is an initial increase in the probability of elephant presence with increasing dominant scale until a certain level after which the probability of elephant presence declines with increasing dominant scale (fig. 7.8a). The probability of elephant presence-dominant scale regression functions for 1980s and 1990s explain 65 % and 68 % of the variance in the probability of elephant presence respectively. Furthermore, it can also be observed that as the intensity of spatial heterogeneity increases, there is a concomitant increase in the probability of elephant presence until a certain level and then the probability of elephant presence begins to saturate or even decrease
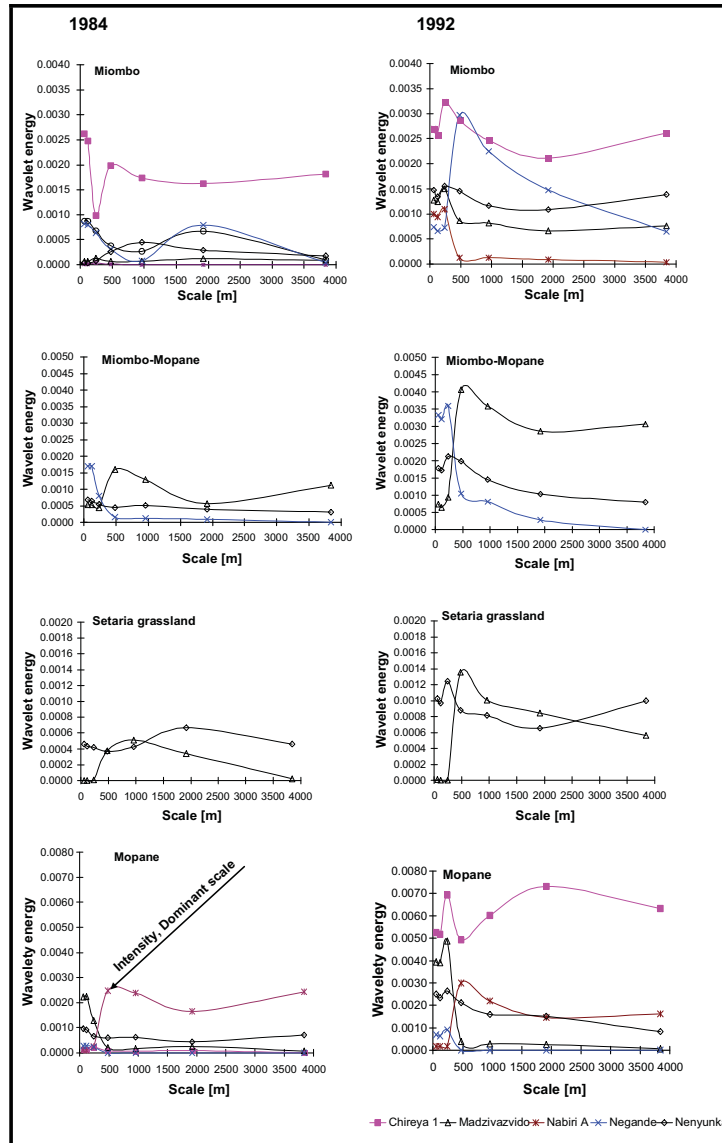
Figure 7.6: Selected wavelet energy functions illustrating variations in intensity and dominant scale in different wards and vegetation classes in 1984 and 1992. The arrow shows an example of the determination of the intensity and dominant scale of spatial heterogeneity from a wavelet energy function.
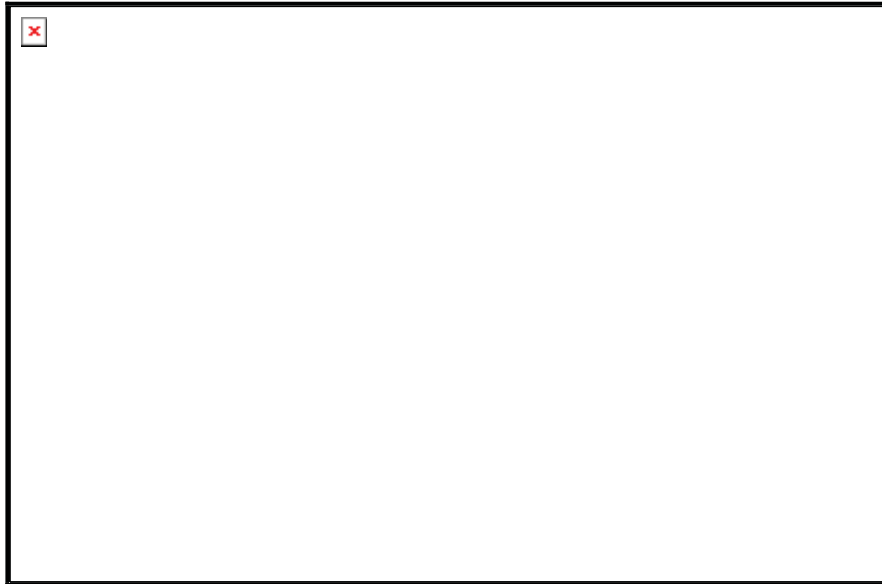
Figure 7.7: The spatial distribution of total wavelet energy per pixel at different scales (wavelet spans) across different wards in 1984 and 1992, as well as in selected vegetation class polygons (the total wavelet energy for the image was divided by 1000000 and then stretched between 0 and 20 to enhance the wavelet energy for visual presentation). The polygon contained in a larger box depicts Setaria predominantly in Nenyunka ward while the polygon contained in the smaller box is Miombo-Mopane vegetation class in Madzivazvido ward.

(fig. 7.8b). The regression functions for 1980s and 1990s explain 61 % and 71 % of the variance in the probability of elephant presence respectively.

Fig. 7.9 shows the probability of elephant presence as a significant ($p < 0.05$) function of both the dominant scale and the intensity of spatial heterogeneity in 1980s and 1990s. It can be observed that a combination of low intensity of spatial heterogeneity and large dominant scales of spatial heterogeneity is associated with a low probability of elephant presence. For example, it can be observed the Setaria vegetation class in Simchembo ward, had a combined low intensity and large dominant scale in the 1980s and it was associated with a low probability of elephant presence (fig. 7.9a). In addition, it can be observed that the
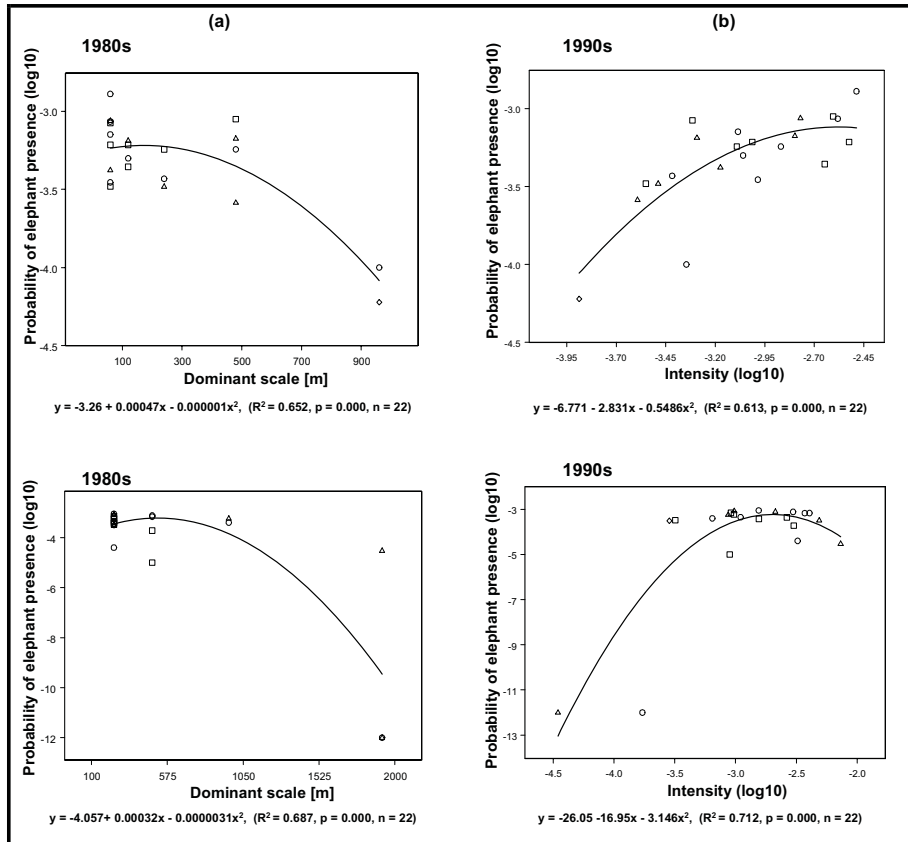
Figure 7.8: Significant (p < 0.05) relationships between the probability of elephant presence and the (A) dominant scale of spatial heterogeneity and (B) intensity of spatial heterogeneity (intensity) in the study area in the 1980s and 1990s in (○) Miombo, (□) Mopane, (◇) Setaria Grassland and (△) Miombo-Mopane floristic-physiognomic vegetation classes.

Miombo vegetation class in Nemangwe 5 ward had a combined low intensity and large dominant scale in the 1990s that was associated with a low probability of elephant presence (fig. 7.9b). It can also be observed that agricultural fields covered most of Nemangwe 5 in 1992 (fig. 7.5). Next, it can be observed that the probability of elephant presence is high in environments where the intensity of spatial heterogeneity is high at intermediate dominant scales of spatial heterogeneity, namely around

480 m. For example, it can be observed that the Miombo-Mopane vegetation class in Madzivazvido has an intermediate dominant scale of spatial heterogeneity and a high intensity of spatial heterogeneity that are associated with a high probability of elephant presence (fig. 7.9). All in all, the regression functions of the 1980s and the 1990s explain 80 % and 93 % of the variance in the probability of elephant presence respectively.

Relationship between elephant presence and changes in spatial heterogeneity

After, analysing how spatial heterogeneity is related to the probability of elephant presence from sampling unit to sampling unit, we also analysed whether changes in spatial heterogeneity in the sampling units over time explained the changes in the probability of elephant presence between the early 1980s and the early 1990s. Fig. 7.10 shows that spatial changes in the probability of elephant presence between the early 1980s and the early 1990s were significantly ($p < 0.05$) related with changes in dominant scale and intensity of spatial heterogeneity in the sampling units between the same periods. It can be observed that a combination of an increase in intensity of spatial heterogeneity and a decrease in the dominant scale of spatial heterogeneity were associated with a decrease in the probability of elephant presence in the study area. On the other hand, a decrease in the intensity of spatial heterogeneity in combination with an increase in the dominant scale of spatial heterogeneity is also associated with the decrease in the probability of elephant presence. For example, a combination of the decrease in the dominant scale of spatial heterogeneity and the increase in intensity of spatial heterogeneity in Setaria in Nenyunka ward were associated with a decrease in the probability of elephant presence (fig. 7.6, fig. 7.7 and fig. 7.10). Concurrently, an increase in agricultural fields in the same land unit between 1984 and 1992 can be observed (fig. 7.5). In addition, a combination of the increase in dominant scale of spatial heterogeneity and the decrease in intensity of spatial heterogeneity in the Mopane vegetation class in Nemangwe 5 ward was associated with a decrease in the probability of elephant presence (fig. 7.6, fig. 7.7 and fig. 7.10). Also, a concurrent increase in agricultural fields in the same land unit between 1984 and 1992 (fig. 7.5) can be observed. In contrast, it is apparent (fig. 7.10) that a combined increase in the intensity of spatial

153

heterogeneity and dominant scale of spatial heterogeneity was associated with an increase in the probability of elephant presence up to a certain level and then it decreases. For example an increase in the intensity and dominant scale of spatial heterogeneity in the Miombo vegetation class in Nabusenga was associated with an increase in the probability of elephant presence (fig. 7.10) The regression function explained 89 % of the variance of the change in probability of elephant presence between the 1980s and 1990s.
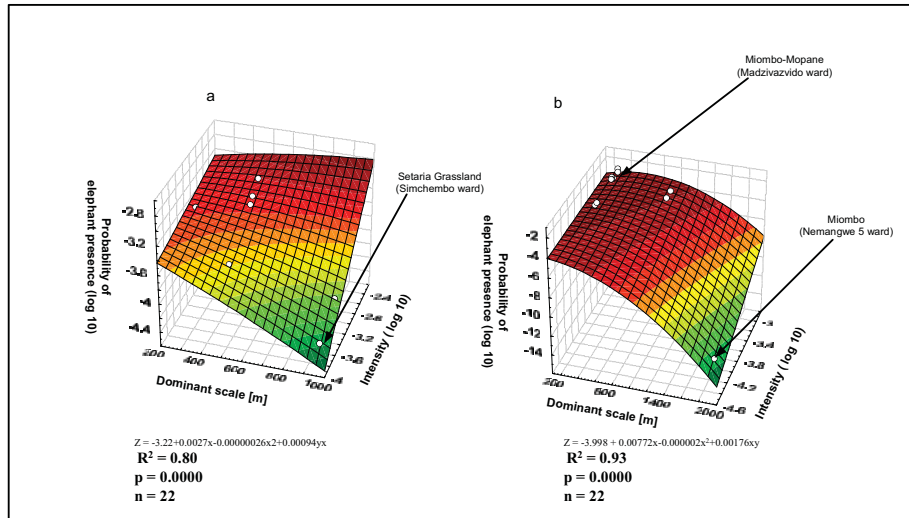

Figure 7.9: A significant (p < 0.05) relationship between the probability of elephant presence and the intensity and dominant scale of spatial heterogeneity plus their interaction in the early (a) 1980s and (b) 1990s. The graph surface represents increasing probability of elephant presence from green (lowest probability) to deep red (the highest probability of elephant presence).
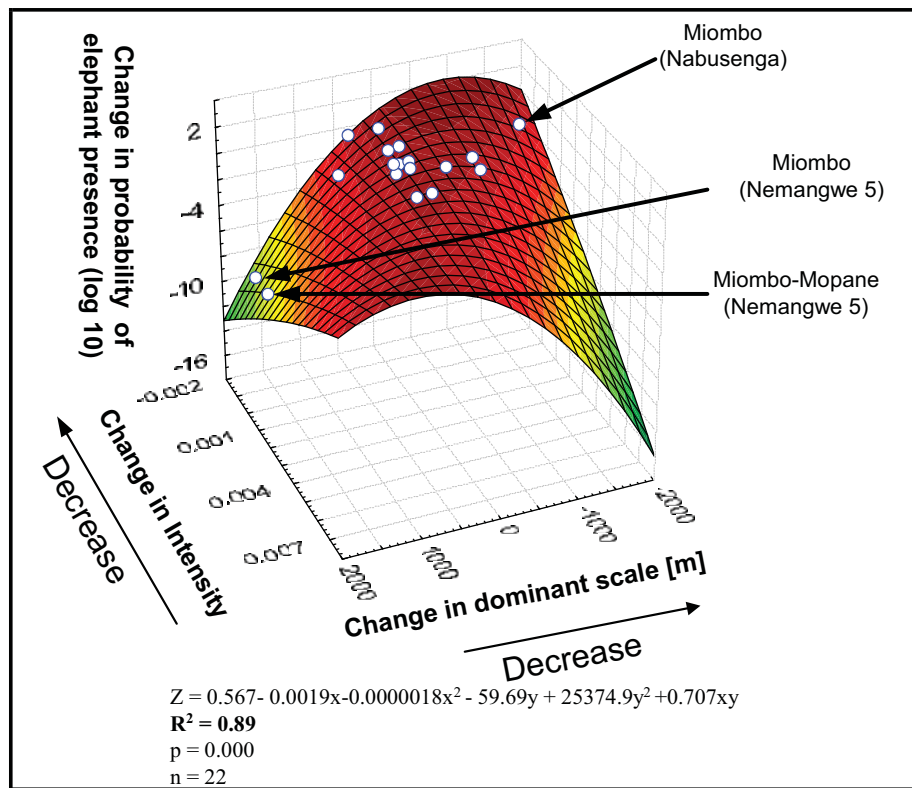
Figure 7.10: A significant (p < 0.05) relationship between change in the probability of elephant presence and changes in the intensity and dominant scale of spatial heterogeneity between the 1980s and 1990s. On all axes, positive values indicate an increase, negative (-) indicate a decrease and zero (0) indicates no change. The green on the graph surface represents a greater decrease in the probability of elephant presence and deep red represents an increase in the probability of elephant presence.

7.4 Discussion

Spatial heterogeneity and the probability of elephant presence in space

Murwira and Skidmore (2003) demonstrated the utility of wavelets in characterising spatial heterogeneity from the dominant scale and intensity perspective. Using wavelets to analyse spatial heterogeneity from this

perspective, the findings in this study have demonstrated a temporally consistent (i.e., in the 1980s and the 1990s) near unimodal (i.e., the relationship describes mainly the descending part of a unimodal model) elephant presence-spatial heterogeneity relationship along the dominant scale and the intensity gradients across 22 land units (fig. 7.8 and fig. 7.9). This result is consistent with the unimodal species distribution or limiting factor models, such as the species-productivity (Wang*, et al.* 1999, Wang*, et al.* 2001) and the species-altitude (Wang*, et al.* 2002) models, except that in this case, it is spatial heterogeneity that is limiting to the distribution of elephants. However, the fact that only the descending part (i.e., from intermediate dominant scale to large dominant scale) of the unimodal relationship is pronounced is because the study area is largely constituted by intermediate to large dominant scales of spatial heterogeneity but not a full range of dominant scales of spatial heterogeneity that include small dominant scales. This finding (i.e., unimodal relationship) is invaluable for landscape planning that takes elephant conservation into consideration because spatial heterogeneity could be manipulated to suit a threshold favourable for both elephants and humans.

Moreover, results on the bivariate elephant presence-intensity and the elephant presence-dominant scale relationships shade the first light on how elephants interact with spatial heterogeneity. For example, the elephant presence-intensity relationship, demonstrates that elephants tend to prefer environments with high intensity of spatial heterogeneity (i.e., with high variability) in vegetation cover compared with areas with low variability (fig. 7.5, fig. 7.8b) (see Chapter 1). An investigation by Murwira*, et al.* (2003) demonstrated that intensity of spatial heterogeneity correlates strongly with the NDVI average and the NDVI coefficient of variation that estimate the amount of cover and its variability respectively. Therefore, since high intensity or variability represents a spatially complex vegetation cover pattern, this confirms the observation that elephants in the Sebungwe associate with areas of high vegetation density and variability to maximise their chances of finding food and shelter (Guy 1976b). However, the fact that this relationship either saturates or even decrease at high intensity values imply that as the variability in vegetation cover increases beyond a certain level, it either no longer has an effect on elephant presence or it even results in a negative trend (fig. 7. 8b) just like

in the species richness-productivity relationship (Said 2003). But it may as well be partly due to the related influence of the dominant scale of spatial heterogeneity, i.e., the patch dimension at which the intensity is manifested because the quadratic elephant presence-dominant scale relationship indicated that elephants prefer intermediate dominant scales of spatial heterogeneity but avoid relatively small and relatively large dominant scales of spatial heterogeneity (fig. 7.8a).

Furthermore, this study demonstrated that a comprehensive understanding of the elephant presence-spatial heterogeneity relationship could only be satisfactorily enhanced if both intensity and dominant scale are used in the analysis (see Chapter 1). In this regard, the results showed that the peak probability of elephant presence is defined by high intensity (high variability in vegetation cover) that occur at intermediate dominant scales of spatial heterogeneity (i.e., around 480 m) that reflect environments characterised by intermediate patch dimensions of natural vegetation and fewer agricultural fields (fig. 7.5 and 7.10). In contrast, lower probabilities of elephant presence are associated with: (1) environments with low intensity (low variability in vegetation cover) that occur at large dominant scales of spatial heterogeneity (descending limb of the unimodal curve), and (2) environments that have small dominant scales of spatial heterogeneity (ascending limb of the unimodal curve) (fig. 7.9). The former coincides with environments that are dominated by grasslands and agricultural fields (fig. 7.5 and fig. 7.9) while the latter coincides with environments dominated by small patches, suggesting (as mentioned earlier) that elephants avoid environments that are largely open (grasslands and agricultural fields) and environments that are dominated by small vegetation patches respectively.

The determination of wildlife species-specific thresholds of the spatial distribution of habitats is critical for the effective management of wildlife species but the perpetual and troubling question has always been whether these thresholds can be ecologically relevant (Jansson 2002). Given the prominence of the community based wildlife management programmes, such as CAMPFIRE, whose existence is rooted in the sustainable utilisation paradigm (Hulme and Murphree 2001), we feel that our findings are ecologically relevant by giving an indication of the kind of optimum or threshold environment that may encourage human-elephant

coexistence, namely high intensity (i.e., high variability) in vegetation cover at intermediate dominant scales of spatial heterogeneity (i.e., around 480 m), as well as environments that elephants tend to avoid (fig.7.9).

Changes in spatial heterogeneity and the probability of elephant presence

Our findings demonstrated that the changes in elephant presence between the early 1980s and the early 1990s were unimodally related to changes in spatial heterogeneity, suggesting that elephants are repulsed by extreme changes of spatial heterogeneity while intermediate changes of spatial heterogeneity may encourage elephant persistence in the landscape. In fact, the results demonstrated that elephants relocate when an increase or decrease in the intensity of spatial heterogeneity occurs together with a decrease in dominant scale of spatial heterogeneity, or a decrease in intensity occurs together with an increase in the dominant scale of spatial heterogeneity. This suggests that elephants avoid areas that are increasingly being dominated by either: (1) small patches irrespective of the level of the intensity or maximum variability in vegetation cover or (2) large patches with a predominantly low intensity or maximum variability in vegetation cover, e.g., grasslands or agricultural fields. In contrast, elephant presence increased or remained constant with intermediate increases or no change in both intensity and the dominant scale of spatial heterogeneity, suggesting that elephants prefer environments that remain unchanged in terms of the levels of spatial heterogeneity. Consequently, we deduce that a combined change in the intensity and dominant scale of spatial heterogeneity had a significant effect on the probability of elephant presence in the communal lands of the Sebungwe region between the 1980s and 1990s.

7.5 Conclusions

We tested whether and how elephants were related to the wavelet transform derived-intensity and dominant scale of spatial heterogeneity. We also tested whether and how changes in elephant presence were related to changes in the intensity and the dominant scale of spatial heterogeneity across different sampling units in the study area between the early 1980s and the early 1990s. Therefore, some conclusions and management recommendations were drawn from the results. Firstly, we concluded that

the wavelet transform-based intensity and dominant scale of spatial heterogeneity could reliably and consistently predict elephant distribution in an agricultural landscape. Secondly, we concluded that changes in the intensity and dominant scale of spatial heterogeneity could also reliably predict changes in elephant distribution. Furthermore, we could recommend from the results that management decisions must take into consideration the factor of spatial heterogeneity when planning the amount and spatial arrangements of agricultural fields that could enhance wildlife species persistence for the benefit of CAMPFIRE. Finally, we assert that considering the dominant scale and intensity factors improves the characterisation of spatial heterogeneity from remote sensing that can be useful in predicting other ecological patterns such as the distribution of different wildlife species.